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PrEP: Probability of Encounter between Ports of Entry

A case study of the US-Mexico border

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Abstract

PrEP aims to explore the field of psychophysics as it applies to the movement of adversaries across international borders. This test experiment uses the US-Mexico border as a case study – beginning with certain assumptions regarding the adversary, the model utilizes environmental and population data to estimate risk perception, and predict routes that a smuggler may take. Additionally, I analyze the impact that destination-based attractive forces may have on agent movement. I found that these attractive forces may improve the validity of the model if they carry less influence that the repulsive forces.

PrEP: Probability of Encounter between Ports of Entry

Introduction

Human behavior, particularly in the aggregate, is very complex. Some collective behaviors organize around the interplay of the constituent agents – crowd behavior, bird flocking, and ant trails are examples of this. Complexity science has explored these kinds of behaviors using agent-based models, cellular automata, and network systems. Similar to how physicists use a few general concepts to predict the behavior of complex systems of physical particles, some researchers have successfully combined concepts from physics such as momentum and force fields with agent-based models to predict collective human behavior. Dirk Helbing performed research on crowd dynamics using this method, and described agents within crowds as being influenced by "social forces".

The original concept for agent-based models stems from the field of artificial intelligence. An intelligent agent is an entity that can sense its surroundings, perceive the objects in them, make decisions based on a goal and its understanding of its current condition, and proceed to action. Agent-based modeling takes these four factors into consideration in creating computational models that simulate the movement of individual agents, with the goal of assessing the movement of agents in general.

One of the challenges in applying precise physics analogies to imprecise, less deterministic areas like human behavior is the difficulty of quantifying principle interactions. The field of psychophysics has traditionally explored the relationship between physical processes and human perception as it impacts behavior.

This raises the question: can psychophysics and related fields provide insights for calibrating physics-inspired agent-based models? PrEP aims to explore this question as it applies to the movement of adversaries across international borders.

Description of PrEP

Our test experiment uses the US-Mexico border as a case study. The illicit transport of radioactive materials across the US-Mexico border poses a threat to the national security of the United States. These materials can be used for a variety of nefarious purposes, such as dirty bombs. US Customs & Border Patrol attempts to intercept such smugglers by placing radiation detection equipment at points of entry; however, it is difficult to do so between designated points of entry. PrEP aims to assess the vulnerability of every possible route across the border to inform requirements for placement of additional resources.

We begin with certain assumptions regarding the adversary and their preferences. Given the fact that they are carrying a very valuable material payload, we assume a sophisticated adversary with experience and resources for planning, and some fore-knowledge of deterrent measures. Additionally, they are moving on foot, and very averse to discovery. The agent will desire a route with limited visibility; therefore, they are more likely to see rugged and normally inaccessible terrain as ideal. Additionally, they will seek out sparsely populated areas with low enemy activity and few obstacles.

With this in mind, the model incorporates geospatial data from four sources. Given that this form of data can be very difficult to compile for such a wide area, we sought out data at a 1-km resolution, so as to ease processing during the experimental stages of this project while preserving the accuracy and precision of the model. The simplest of these is a map of the fence across the US-Mexico border – we assume that adversaries will be particularly averse to areas close to the fence given the increase presence of law enforcement personnel. At the same time, a location will not necessarily be considered more or less ideal than the area immediately surrounding it, given that people don't generally think in strictly numerical terms. As such, we decided to construct several "buffer" regions around the fence, set at 0.5 km, 2 km, 40 km, and everywhere else – close, medium, far, and very far, in essence.

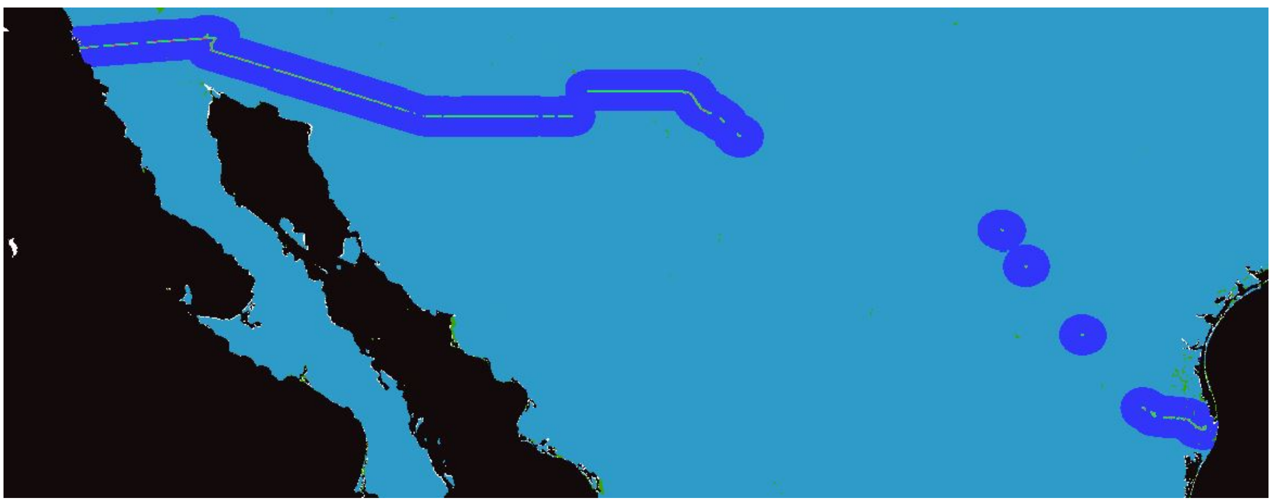

Figure 1. Base map of the US-Mexico border with fence data and buffer regions added.

The next data source necessary is a digital elevation model. From the base data, the slope and roughness can be calculated – these are important given that they imply the ruggedness and therefore visibility of given areas. The slope can be calculated automatically using the Spatial Analyst toolbox in ArcGIS. Topographic roughness can be defined based on the elevation in a variety of ways, depending on the sort of data sought after – we opted for a simple calculation of the standard deviation of elevation, as used by Ascione et al., given that the necessary components were also available in the Spatial Analyst toolbox. We calculated the mean and range of elevations in the 3x3 cell surrounding each point, and then computed the standard deviation using these values.

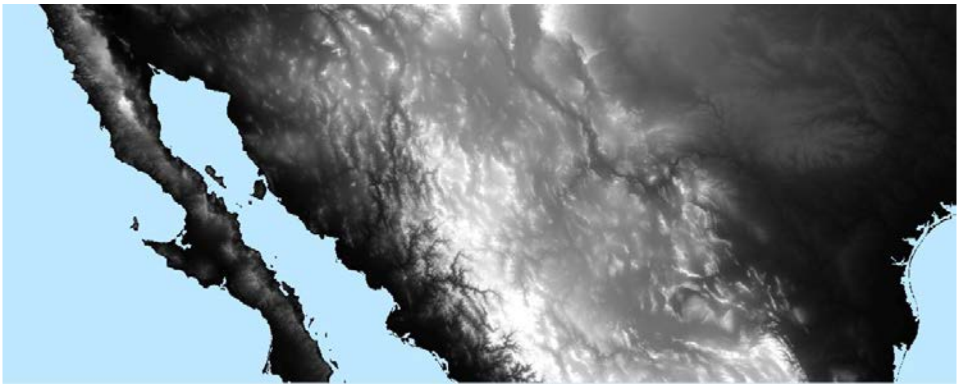

Figure 2. A DEM of the border region, with white areas having the highest elevation.

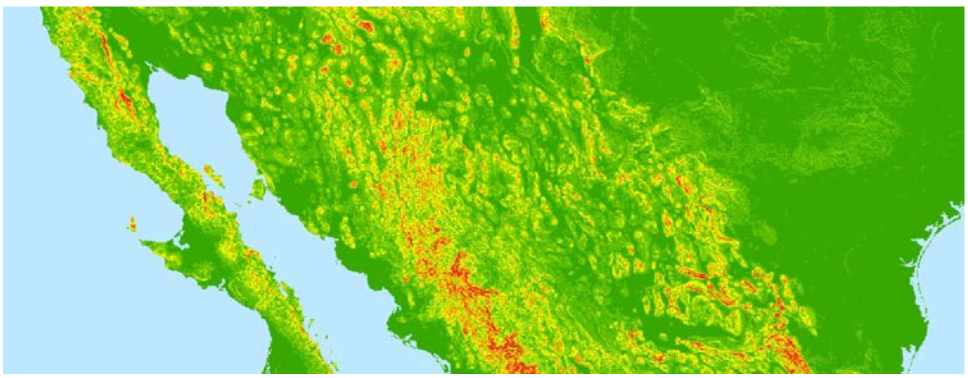

Figure 3. The variations in slope across the border region.

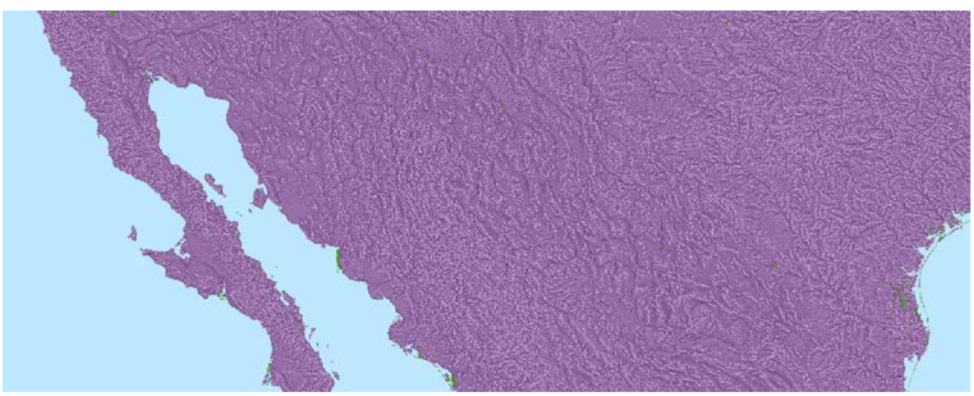

Figure 4. A roughness map of the border region. Areas that have a value of close to 0, whether positive or negative, are the least rough, as they deviate very little from the mean.

The next data source is a land cover classification map. This also has implications for the visibility and ruggedness of the terrain, so we assume that the adversary will prefer areas with dense vegetation as opposed to open land. Considering the fact that adversaries will move by foot, having this data also allows us to ensure that the pathways will not somehow travel through bodies of water. Apart from open water, examples of land cover classifications included are forests (a variety of sorts), grasslands, shrublands, and urban areas.

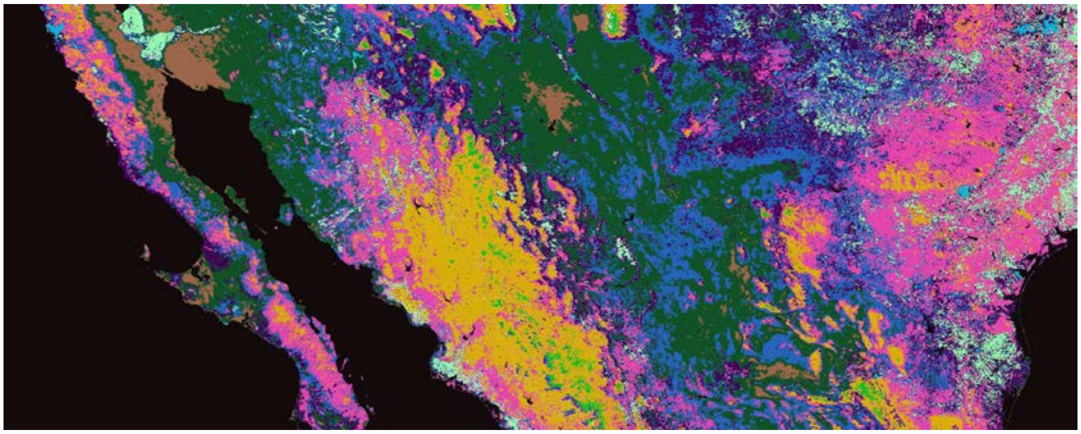

Figure 5. A land cover classification map of the border region.

The final data source is a population density map. Given that the adversary does not want to be detected, they will prefer areas of low population density.

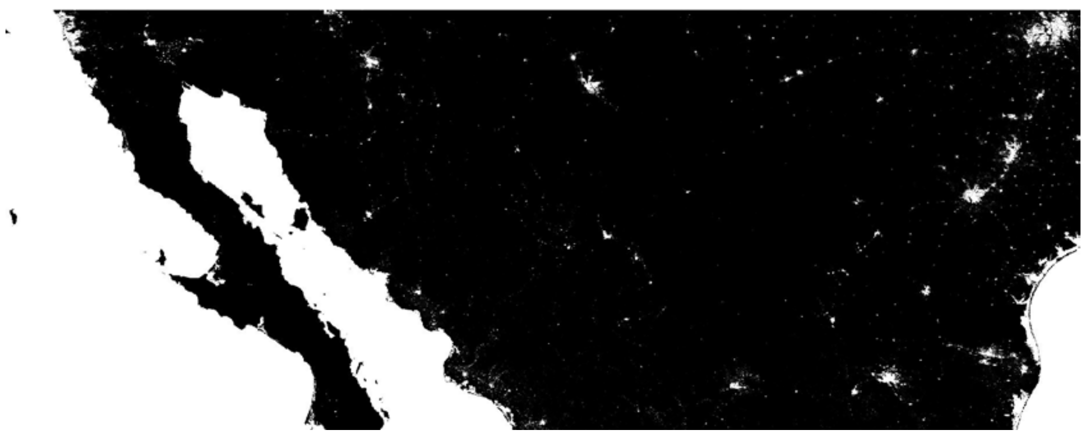

Figure 6. A population density map of the border region, with darker areas being relatively unpopulated.

Using the above data, we use a Bayesian adversary reasoning model. This assesses an adversary's perception of discovery likelihood based on natural and defensive geographic influences. This generates a raster of output probabilities which serves as input to an aversion force-field model. The source of the force field must be scaled logarithmically from the original raster to account for the way humans perceive probabilities.

Term	Prob Range	Scaled Value
"Unlikely"	< 0.3	0
"Even"	0.3 – 0.6	1
"Likely"	0.6 – 0.8	10
"Highly Likely"	0.8 – 1.0	100

Table 1. Linguistic categories, probability ranges, and scaled values.

We treat the discovery likelihood as a "charged" field which creates repulsive forces. From the risk perception field representing charge, we obtain the electric potential through Coulomb's equation, and use the gradient of this to find the field vectors. The agents are influenced by the forces, and deflected from their normal paths. The pathways can then be summed to estimate the probability of encounter at a given point. This was performed initially on a small section of the border region in southern New Mexico to simplify our analyses of the output and refine the model if necessary.

Contributions Made to the Research Project

Apart from gathering and cleaning all of the initial data used in the experiment, I questioned whether or not a bivalent (i.e. positive-negative) force model would be more accurate than a model informed solely by negative influences. I narrowed this down to a destination-based bivalent model, which incorporates the agent's proximity (defined here as the inverse of distance) to a given target as a positive force. There are two ways I thought to do so – by adding an extra node to the Bayesian network to create a "probability of success" map, and by calculating force diagrams for the positive and negative factors separately. The latter was more straightforward, as it didn't require much deviation from the original model; however, the former necessitated that I determine how proximity and probability of discovery should be combined to produce a single probability. Dividing proximity into linguistic categories, as was done with probability of discovery, made this quite simple.

	Very High	High	Medium	Low
Unlikely	1	0.75	0.5	0.25
Even Odds	0.75	0.5	0.25	0.1
Likely	0.5	0.25	0.1	0.05
Very Likely	0.25	0.1	0.05	0.01

Table 2. Perceived probability of success determined by proximity (horizontal) and probability of discovery (vertical).

Images detailing the pipeline for this method of incorporating proximity are shown below.

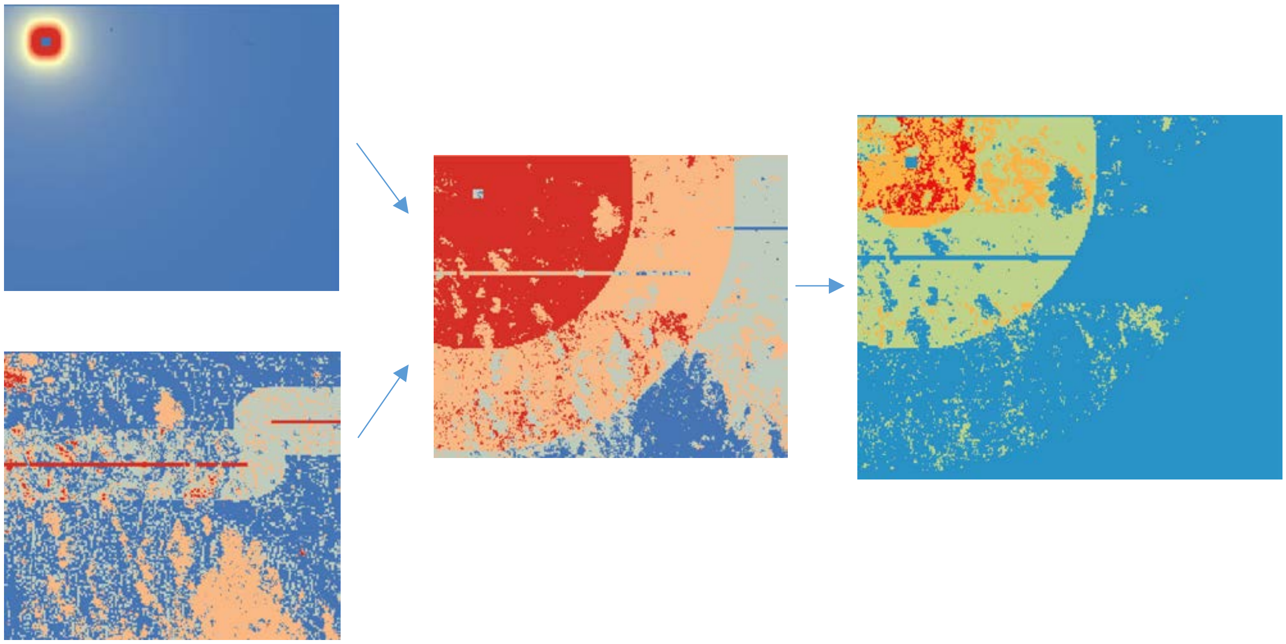

Figure 7. Left to right: proximity & probability of discovery, probability of success, and scaled probability of success.

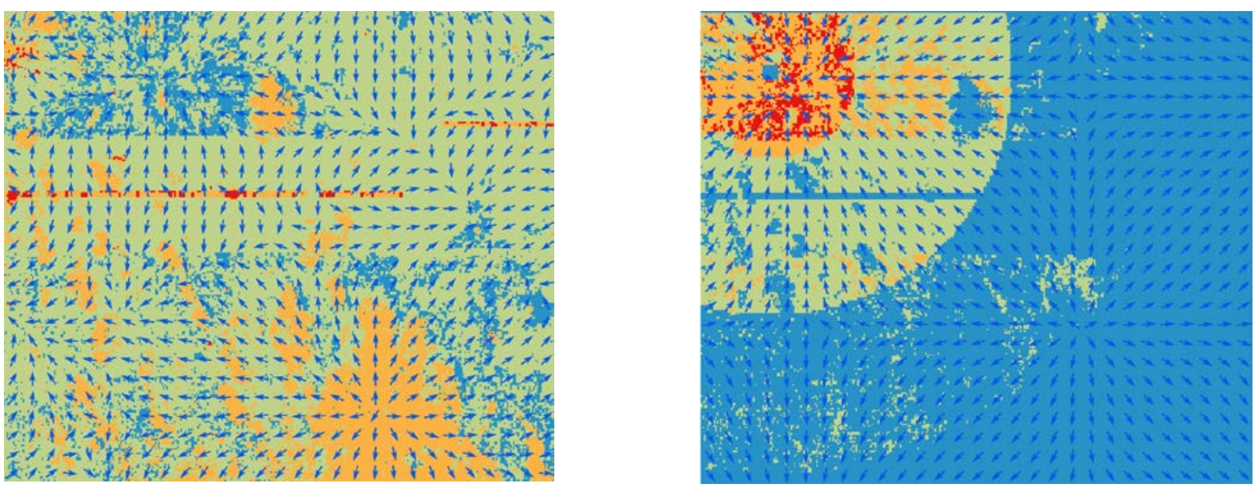

Figure 8. Probability of discovery forces and probability of success forces.

The two maps above show that the probability of discovery and probability of success forces are not accurate enough representations. The probability of discovery field appears to represent the averse forces well, but does not explicitly incorporate a destination. The probability of success field, on the other hand, seems to be too heavily influenced by the destination – it is not likely that an agent would move through the fence, as is shown above. The combined force fields from proximity and probability of discovery show more nuance.

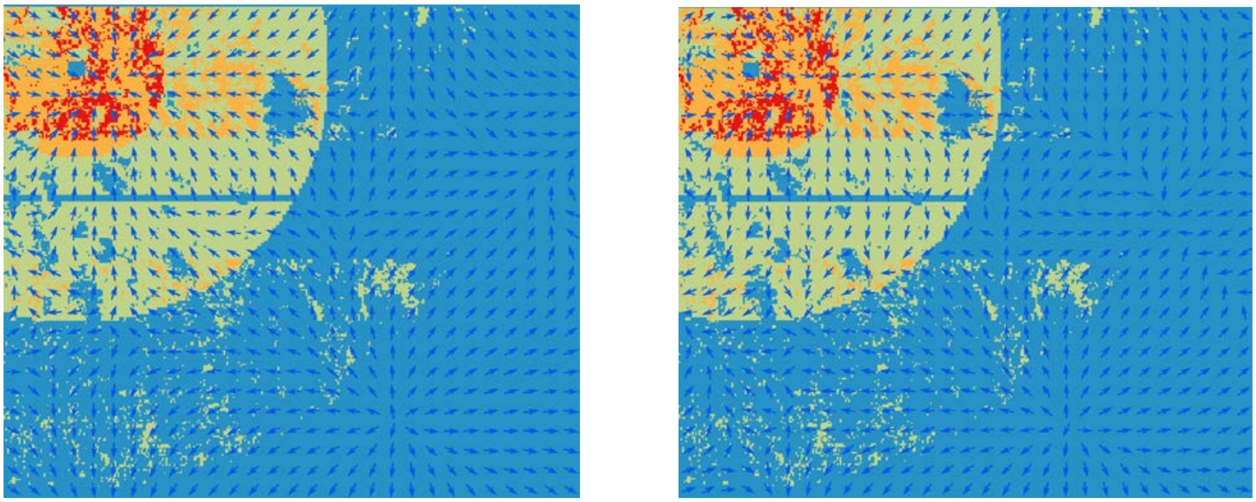

Figure 9. Combined force fields, 1:1 and 10:1 ratios.

Weighing each component equally, the combined field does appear to share characteristics with both the discovery and success fields. However, despite the fact that it is more realistic than the first two fields, it is still evident that the forces are ignoring part of the fence. As such, it makes sense to weigh the forces at a 10:1 ratio, favoring the repulsive field. This represents an agent being drawn to a particular target while remaining very fearful of discovery. With this field, it is clear that the field vectors are generally similar to the probability of discovery vectors on the Mexico side of the border; however, there is more direction towards the specified target on the US side. As such, it appears that a bivalent model that favors aversive forces may be more accurate than a model that only incorporates aversive forces. It has yet to be determined whether or not this will translate to a significant difference in the actual pathways shown in the agent-mover portion of the model.

New Skills and Knowledge Gained

On the most fundamental level, it was very interesting for me to learn about psychophysics in general, which is a field I hadn't had much (if any) exposure to prior to this internship. I spent a lot of my time in the first few weeks doing background research, so I read a lot about the use of psychophysics for a variety of applications. I also had very little experience with web scraping at such a large scale; however, given that I've spent a lot of time using the internet, I quickly became quite good at it. ArcGIS proved to be quite instrumental in visualizing and transforming this data into a useful format.

Research Experience Impact on Academic/Career Planning

Upon beginning this internship, I was pretty sure that I wanted to pursue scientific research as a career. Additionally, I was generally interested in physics and math as fields. However, I was quite unsure of the specifics, and the internship has helped narrow my focus. In general, this project reflects my personal academic interests well; as such, I appreciated the opportunity to explore applied math and psychophysics as it pertains to PrEP. I'm much more concrete in my desire to go to graduate school, as it became evident to me that it's necessary for all of the specific careers that interest me. Additionally, I've become much more open to government-based jobs.

Relevance to the Mission of DHS

Given that PrEP aims to provide insight into the movements of potential terrorists who are smuggling the wherewithal to construct weapons of mass destruction, I am proud to be contributing to a major aspect of the mission of DHS: the prevention of terrorism and enhancement of national security.

References

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Raw data was obtained from the U.S. Geological Survey and the Commission for Environmental Cooperation.